NEURAL NETWORK BASED SPEED CONTROLLER FOR AN 8/6 POLE SWITCHED RELUCTANCE MOTOR

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ABSTRACT

Switched reluctance drive was developed to offer an advantage in terms of efficiency, power per unit weight and volume, robustness, and operational flexibility. They represent a real alternative to conventional variable speed drives in many applications. Due to its simple construction, high-speed operation ability, insensitivity to high temperature, and its features of fault tolerance switched reluctance motor has emerged as an important technology in industrial automation. There are various techniques used for the control of SRM. The common feature of all these techniques is the presence of a rotor position sensor. This is a major disadvantage to the whole system. It is normally necessary to use a rotor position sensor for commutation and speed feedback. The operation of the switching circuit is influenced by signals obtained from the rotor position sensor. The presence of these sensors reduces the reliability, increases the cost and size of the whole system. To ensure the efficiency of the system these sensors must be avoided. Hence a sensorless speed control system is introduced. To achieve this the Adaptive Neural Network (ANN) technology is used in the controller for fast and accurate response, adaptability, and stability. Neural network using feedforward network reduces the complexity of the whole system. By incorporating ANN in switched reluctance motor, the calculations become simpler and its implementation is easy. In this paper, a neural network-based controller for switched reluctance motor is implemented using MATLAB/Simulink software. The output of the proposed system is compared with the conventional system which makes use of a rotor position sensor.

Keywords: Switched reluctance motor, Rotor position sensor, Adaptive neural network.

INTRODUCTION

Switched Reluctance Motors (SRM) exhibit desirable features including simple construction, high reliability, high fault tolerance capability, high torque density, high efficiency in a wide speed range, and low cost. It is useful to low-cost variable-speed drives in many industrial applications [1]. The presence of a rotor position sensor increases the cost as well as the size of the whole SRM control system [2]. In recent years, sensorless drive methods have attracted much interest. The sensorless drive method using impressed voltage pulse at enenergized phases is one of the techniques used [3].

This method focuses on the magnetic characteristic of SRM: the magnetic circuit of each phase changes with rotor positions. By injecting high-frequency voltage pulses into unenergized phases, the related current pulses will change with rotor positions [4]. Then, the exciting timing can be obtained by some thresholds which are set at the measured current pulse [5]. But it has some drawbacks.

The control of SRM drives depends on the phase current, absolute rotor position, and rotor speed signals to obtain closed-loop control of torque and speed. Depending on the quality of performance required for a particular application, such as for low performance, the phase current and speed signals may be dispensed within the control system. The feedback signals are usually measured with transducers, which increases the cost of the electronic controller and its packaging size. In the presence of a rotor position or speed transducer, the size of the motor housing and the cost are increased significantly [6]. The requirement of low cost with high performance for motor drives has placed the agenda of low cost, sensor-based, or sensorless technology at the forefront of present-day research and development of motor drives.

Before the advent of fuzzy logic control (FLC), speed control is done by the PID controller, but FLC tracks the exact speed response than the PID controller [7]. By analyzing the performance of FLC and PID control, FLC possesses artificial intelligence and a rule-based system. It controls the speed in a highly appreciated manner [8]. Sensorless control algorithms can be used for SRM control in diverse applications to obtain reliable operation. The efficient functioning of these motors can be ensured by using adaptive computational techniques. It has the advantage of a strong capability of handling uncertain and nonlinear information. The use of adaptive algorithms in SRM modeling and control has been extensively studied in the past few years [8].

In this paper, a sensorless speed control technique using an artificial neural network controller is proposed. It eliminates the use of a rotor position sensor to achieve speed control of the motor. The model is implemented using MATLAB Simulink software.

CONTROL PRINCIPLE

With Faraday's law, the p^{th} phase voltage balance equation of the three-phase SRM can be expressed as

$$\frac{d\psi p(ip,\theta)}{dt} = v_p - R_p i_p, \qquad p = 1, 2, 3,$$

where ψ_p, v_p, R_p, i_p and θ are stator phase flux linkage, stator phase voltage, stator phase resistance, stator phase current, and rotor position, respectively. If the effect of mutual inductance is ignored, the stator flux linkage can be described as

$$\psi_p = L_p(\theta, i_p) \cdot i_p,$$

where $L_p(\theta, i_j)$ is the phase self-inductance.

The most general expression for the electromagnetic torque at any position can be represented as

$$Te = \frac{dWc(\theta,ip)}{d\theta} \mid ip = constant = \frac{dWs(\theta,ip)}{d\theta} \mid \psi p = constant$$

where T_e is the electromagnetic torque,

$Wc = \int_0^i \psi(\theta, i)\, di$ is the co-energy,

$Ws = \int_0^\psi i(\theta, \psi)\, d\psi$ is the stored field energy.

By neglecting the saturation field effects in SRM, the self-inductance L_p becomes independent of the current i_p. In this case, the electromagnetic torque T_e can be expressed as

$$Te = \frac{1}{2}\frac{dL_p(\theta)}{d\theta} i_p^2 = \frac{1}{2}\left(\frac{dL_p(\theta)}{d\theta} ip\right) i_p = K_t(\theta, i_p) \cdot i_p$$

where $K_t(\theta, i_p) > 0$ denotes the torque coefficient.

The electromagnetic dynamic equation of the switched reluctance motor and loads can be expressed as

$$\frac{d\omega}{dt} = \frac{1}{J}(Te - k_\omega \omega - T_L),$$

where J, k_w, and w are the moment of inertia, the viscous frictional, and the rotor speed, respectively. T_L is the external load torque.

In practical applications, the SRM operates under different working conditions, which will lead to changes in the parameters of the motor. Hence, the real parameter consists of two parts, the nominal value and their variations [6].

SPEED CONTROL USING NEURAL NETWORK

A sensorless control system including an 8/6 poles four phases SRM is built with MATLAB/Simulink as shown in figure 1.

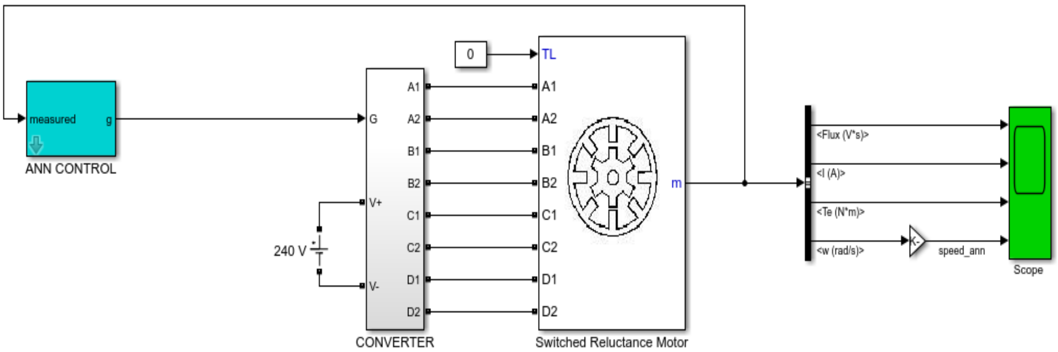

Figure 1. Simulink model of the SRM control system.

Table 1. Simulation parameters.

Phase	4
Stator poles	8
Rotor poles	6
Input voltage (V)	240
Stator resistance (Ω)	0.05
Friction coefficient (Nms)	0.005
Moment of inertia (kg m2)	0.01
Power (kW)	75

3.1 Feedforward Neural Network

The feedforward neural network consists of three layers. The first being the input layer consists of one neuron which is provided with the estimated speed. Here the tan sigmoid transfer function is used as the activation function. The hidden layer consists of 5 neurons and here also tan sigmoid activation function is used. The output layer uses the linear transfer function as the activation function.

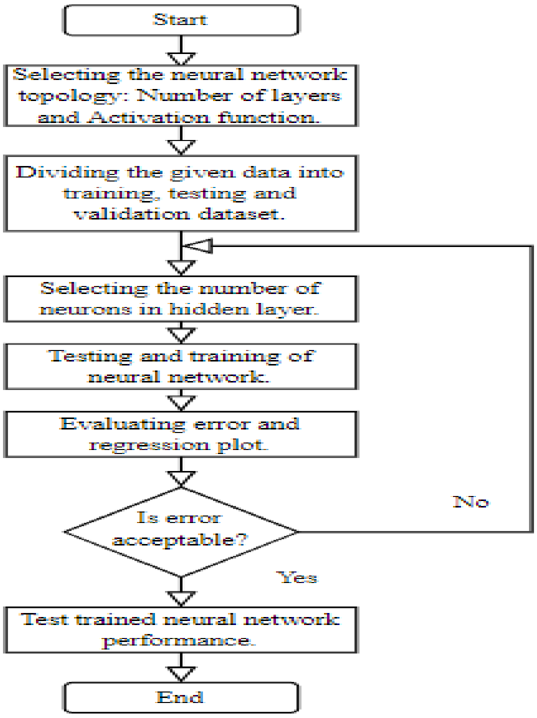

Figure 2. Flowchart for the feedforward neural network.

SIMULATION RESULTS

The neural network-based controller for the switched reluctance motor is simulated using MATLAB/Simulink software.

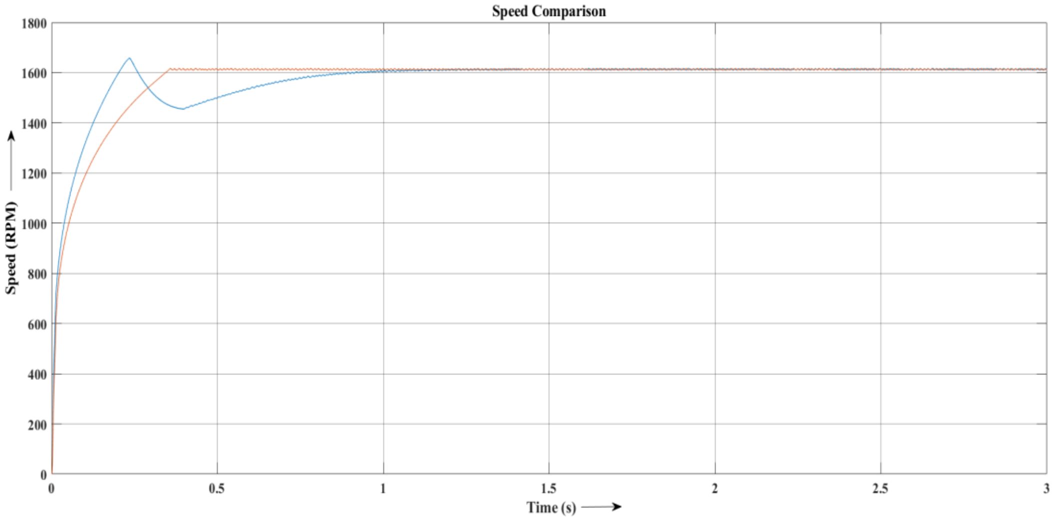

Figure 3. Comparison of the output speed of the simulation model with neural network controller (Blue curve) and position sensor (Red curve).

From the comparison shown in table 2, it is clear that the conventional model making use of a position sensor is not settling to a specific speed. This will affect the effective function of the SRM. This problem is mitigated by using the proposed system as it helps the speed to converge to a specific value. In the case of the rise time, the proposed model takes lesser time.

Table 2. Comparison of the parameters of the conventional and the proposed system.

Parameters	**Conventional model**	**Proposed model**
Rise time(ms)	219.794	140.932
Settling time(ms)	Speed is not settling.	176.744

CONCLUSION

A sensorless control system for switched reluctance motors using an adaptive neural network has been proposed. The detailed operating waveforms are presented. The proposed controller was implemented using MATLAB Simulink software. The sensorless model was implemented on an 8/6 pole switched reluctance motor. The training of the neural network was done using the levenberg marquardt algorithm. The simulation results demonstrated the effectiveness of the neural network controller over the model using the rotor position sensor.

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